Integrated strategy for porosity mapping using genetic inversion on heterogeneous reservoir

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SUMMARY

Seismic reservoir characterization is the stat-of-art in using various source of data. Generally, seismic data, due to their low resolution are randomly used in the final steps of reservoir characterization. However, large coverage of 3D seismic data, compared to well data, make it possible to be applicable for distribution of characters through the whole reservoir. In this regard, seismic data should be inverted to illustrate desired characters through the media. Conventionally, seismic inversion is performed using well logs which have defects in its derivation steps, such as wavelet extraction and its propagation through media. The proposed strategy to resolve such deficiencies, is the genetic inversion. However, genetic inversion has its own deficiency in accuracy. In this study, we propose an integrated strategy for using various source of data in an iterative manner for resolving this obstacle. The proposed strategy, uses combined related attribute to evaluate initial acoustic impedance inverted model by genetic inversion. The model then would be updated to satisfy well data. The proposed strategy was applied on a heterogenous reservoir from south west of Iran. Three seismic attributes were integrated to produce a unique attribute for initial model evaluation. The final model then was evaluated by well data and compared with the conventional method of seismic inversion. Result of the proposed strategy in genetic inversion depicted improvement in final acoustic impedance model and porosity distribution model.

Key words: Seismic reservoir characterization, Genetic inversion, Seismic attributes, Porosity distribution.

INTRODUCTION

Accurate representation of the subsurface geological structure and rock properties model is an essential part in respect of reservoir characterization [1]. Various advanced methods are used to derive precise model of reservoir characteristics and provide information at many different scales [2]. Seismic reservoir characterization in heterogeneous reservoirs is essential to resolve some of ambiguities in reservoir management. Previous studies have shown that homogeneity of the porous media has the highest efficiency in production (namely 40%), while its efficiency vanishes in heterogeneous media to 37% [3], [4]. Thus, the practical approach consists of incorporating the impact of the reservoir heterogeneity in modeling reservoir characters [5]. Therefore, obtaining an accurate three-dimensional model of reservoir properties, such as porosity and permeability, would be required. Through this procedure, acoustic impedance data and the derived porosity distribution facilitate studies of lithology, compaction and fluid flow in the carbonate reservoirs [6]. A successful seismic-based reservoir properties estimation effort has three steps: accurate seismic inversion in 3D to obtain relevant reservoir characters, rock properties transformation to relate reservoir characters to the seismic parameters and mapping these parameters in 3D. This problem is non-unique and thus any available information, specifically geologic interpretation, should be used to improve ability to infer the reservoir properties of interest with confidence [7]. However, obtaining accurate and precise relation between seismic parameters, which is the main source of information in seismic reservoir characterization is a challenging task, specially in heterogenous reservoir, even with simple structures [8]. Various studies have shown that distribution of reservoir characteristics, as porosity and permeability, depends on the rock properties of the reservoir, which could be extracted from seismic attributes [9]. Thus, several studies have been performed on introducing seismic attributes in various strategies for seismic reservoir characterization. However, seismic attribute by itself is not a reliable source of information, which requires combination of various seismic attributes in any proposed strategy for seismic reservoir characterization [10]. This implies of perform a literature review on selection of attributes for desired reservoir characteristic and subsequently, an appropriate strategy for integration of the selected attribute, to obtain a reliable unique map [11]. However, seismic attribute by itself could not be used directly for extraction reservoir characters, but it should be used for an intermediate product or evaluation of the intermediate product, as the acoustic impedance [12]. Mostly selected attributes, or any integrated attribute would be used for evaluation of the seismic inversion result. However, since the acoustic impedance conventionally is obtained by other source of information, as sonic and density logs, evaluating its result is not rationally acceptable [13]. In this study, we introduce a procedure for obtaining inversion result in such a way that could be evaluated by a combined unique attribute result. The proposed strategy here then would be applied on two target horizons from a same oil field in south west of Iran.

METHOD AND RESULTS

The main components of a general workflow for seismic inversion on reservoir characterization consists of solving local auxiliary problems in target formation on seismic cube, formal upscaling of the obtained results to build a coarse scale equation and global solving of the upscaled coarse scale equation [14], [15]. The proposed strategy aims to resolve some of the ambiguities in the procedure of seismic inversion, required for further reservoir characterization. Obviously, result of the inversion procedure depend on the quality and accuracy of the interpretation step, which itself is result of accurate and precise processing [16]. As an assumption, it is assumed that the processing procedure was applied adequately on data, which make it appropriate for further interpretation. Thus, the whole procedure could be observed in three steps, the interpretation step, the inversion and attributes analysis and finally rock properties analysis, which is known also as a simplified seismic reservoir characterization. The interpretation step is divided into two separate parts as the seismic structural interpretation and time – depth conversion using velocity analysis. The interpretation steps performed on data in detail, consists of well data analysis, generation of synthetic seismogram for all the wells, (required for primary inversion) followed by seismic-well tie and attribute analysis, combined with seismic texture classification to increase accuracy of seismic horizon identification. Interpolation and extrapolation of seismic characters using seismic attributes between and beyond wells here could be performed by incorporation of seismic and other soft information via Co-Kriging. However, it is strongly depending on the availability of properly sampled data sets. It is proposed that in case of large variation in seismic properties, the principal component analysis of seismic attributes could be appropriately used. However, linear discrimination works satisfactorily when two classes are involved and the classification boundary is not very complicated. It should be noted that in one hand, due to the simplicity of structural modeling in the study filed, and in the other hand, due to presence of large number of available wells, 200 m space away from each well was selected for matching correlation between well tops and picked horizons. Subsequently, time structural maps for all the selected horizons were obtained followed by velocity model building step, required for time – depth conversion (TDC). Since the TDC step is an important part of initial interpretation, which strongly affect result of the further reservoir characterization by seismic data, thus it is required to perform this step with most appropriate method. In this regard, the velocity cube was prepared by four different methods and the most appropriate result was used for depth conversion and depth structural mapping. After finalizing the interpretation step, the initial inversion procedure was performed for initial modelling of acoustic impedance for total seismic cube, especially for the main reservoir zone by genetic inversion. Then it was followed by selection of some related attributes, as variance, envelop and instantaneous frequency for neural network estimation, after analyzing and indicating high correlation among the inversion parameters. The neural network training is also required for feature classification on target formations by facies changes. According to the characteristic of seismic data and seismic facies of the target formation, various methods could be proposed for neural network analysis. Here we propose to use Kohonen's self-organizing map (K-SOM) method. However, a dataset may be defined by any combination of attributes and K-SOM generates topologically related clusters. The method generates coordinates of cluster centers with given attribute coordinates. However, it does not relate the cluster to any physical or reservoir condition. This has to be done in the calibration step. An important note for seismic data here is that if the system could not be trained properly, it will recognize and correctly classify only those cases included in the training set, while any new seismic feature which was not included in the training set will be misclassified or not recognized. However, these initial steps would be followed by building initial inversion model for effective and total porosity of the target formation. By reducing inconsistency of inversion result and rock properties model using well log data and/or core analysis, simple grid model, layering, zonation and geometrical modeling could be performed for enhanced inversion procedure. This procedure consists of generating final inversion model for acoustic impedance on target formation by the genetic inversion method, which is followed by enhanced effective porosity modelling for target formation. The whole evaluation process could be performed using comparison of cross plot diagrams (between models and wells). Moreover, qualitative uncertainty associated with the different predicted values (i.e. confidence interval and estimate of misclassification probability) must be provided as well, so that proper decisions can be made. Thus, it is evident that this involves interdisciplinary effort that includes rock physics, geologic interpretation, and seismic inversion technology. However, for quantitative description of reservoir properties, one must derive a way to quantify the errors and uncertainties associated with the process. Figure 1 shows the proposed strategy, which would be applied on the study field.

Figures and Tables

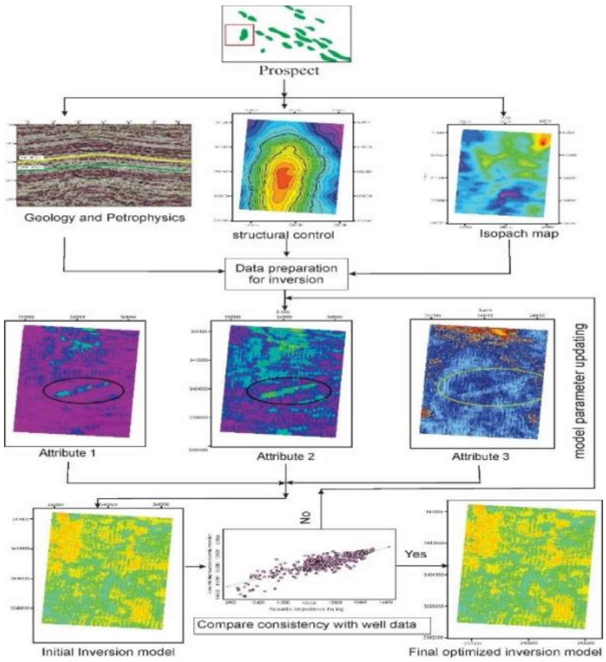

Figure 1. A simplified flowchart of the proposed strategy

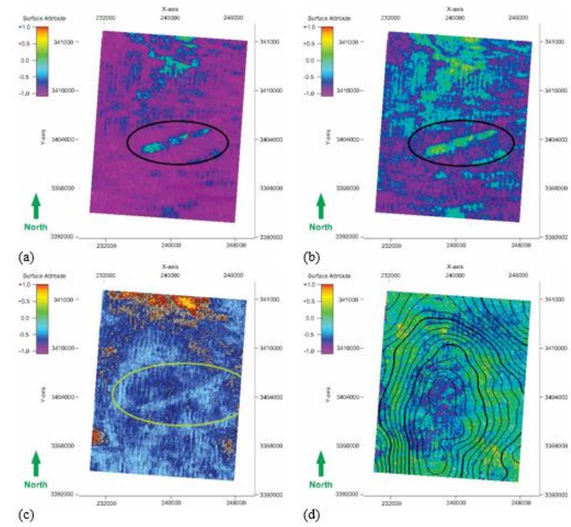

Figure 2. (a) A time slice of the variance attribute of the target formation that shows a lineament in the target. (b) The chaos attribute of the same time which shows chaotic pattern of the study reservoir. (c) The envelope attribute that shows the same lineament and the reservoir structure. (d) The combined attribute image which was obtained based on the correlation values in Table 1.

Table 1, Correlation between different seismic attributes to obtain the most appropriate combination attribute.

	Variance	Envelope	Chaos
Variance	1.0000	0.3953	0.4638
Envelope	0.3953	1.0000	0.5207
Chaos	0.4638	0.5207	1.0000
Total	0.4975	0.5489	0.5916

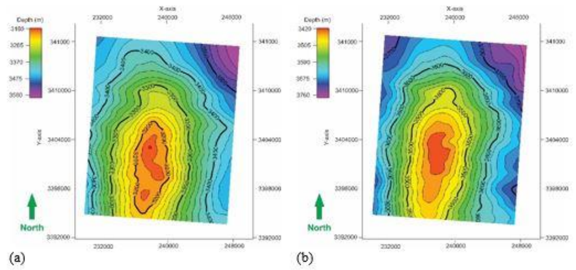

Figure 3. (a) Depth structural model of the first target formation (Sarvak) in the study reservoirs and (b) depth structural model of the other target formation (Fahliyan). Both structural models show an anticline in the study field with gentle dips.

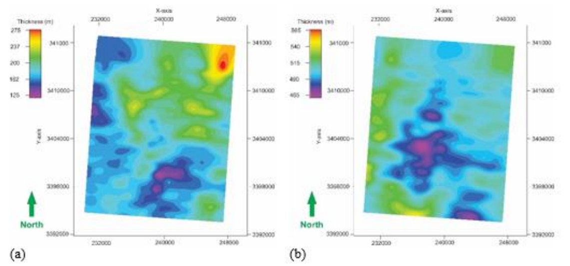

Figure 4. (a) Isopach map of the first target formation (Sarvak) in the study reservoirs and (b) isopach map of the other target formation (Fahliyan). Both maps show thickness of the oil column in the target formations.

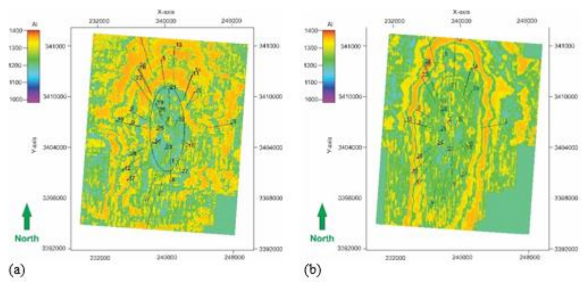

Figure 5. Result of the inversion for the Fahliyan formation by (a) the conventional method and (b) by the proposed strategy.

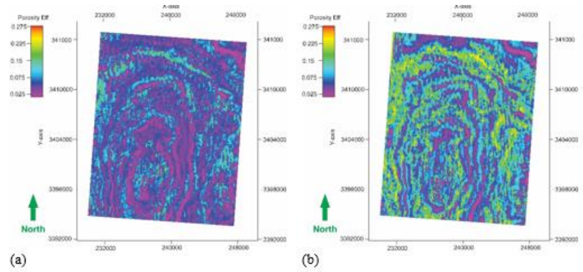

Figure 6- Result of the porosity for the Fahliyan formation by (a) the conventional method and (b) by the proposed strategy.

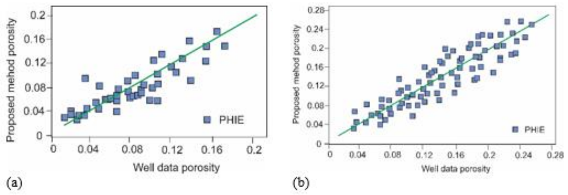

Figure 7- (a) Cross plot for porosity estimated by the proposed method and the conventional method for the Sarvak formation and (b) Cross plot for porosity estimated by the proposed method and the conventional method for the Fahliyan formation. Both cross plots were derived for well number 2, in the center of the reservoir.

CONCLUSIONS

The proposed inversion strategy, which used an integration procedure of conventional inversion procedure used neural network analysis and genetic inversion could resolve some of the ambiguities in conventional inversion. The procedure, however, requires accurate interpretation step both in structural analysis and seismic reservoir properties. In the presented study, interpretation of seismic data and structural modelling revealed that the study reservoir is situated as a gentle type of elongated anticline, which was not strongly affected by tectonic condition. Therefore, it was supposed that the lateral lithofacies changes plays an important role in creation of possible stratigraphic traps. The upper member of the Sarvak formation indicated two parallel series of buildups with ENE-WSW trend. In the trough between two parallel seismic features down lapping reflectors was considered as stratigraphy sedimentary features within small intra-platform depression. Inversion results in the lower part of the Fahliyan formation also indicated good to fair porosity distribution with the result of the proposed strategy. High correlation factor between its impedance and porosity was observed in the Fahliyan formation. Comparison of inversion result and porosity models for two reservoirs with different rock types revealed that the proposed inversion strategy showed more accurate performance in the carbonate intervals.

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Table 2. Correlation values between used attribute for inversion evaluation and the final result of the genetic inversion

	Acoustic Impedance	Envelope	Chaos	Structural smooth	Smoothing variance	Genetic Inversion
Acoustic Impedance	1.0000	0.0035	0.0027	0.2185	0.0015	0.0122
Envelope	0.0035	1.0000	0.4231	0.0047	0.3304	0.1068
Chaos	0.0027	0.4231	1.0000	0.0065	0.5530	0.2910
Structural smooth	0.2185	0.0047	0.0065	1.0000	0.0055	0.0027
Smoothing variance	0.0015	0.3304	0.5530	0.0055	1.0000	0.4229
Genetic Inversion	0.0122	0.1068	0.2910	0.0027	0.4239	1.0000
Total	0.2189	0.4427	0.6129	0.2187	0.6301	0.4384